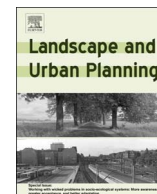




Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Note

Research note: Examining the association between tree canopy, parks and crime in Chicago

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ARTICLE INFO

Keywords:

Environmental criminology
Green space
Negative binomial regression
Spatial autocorrelation
Urban tree canopy

ABSTRACT

Urban green spaces have been shown to benefit residents' physical and mental health as well as strengthen social ties. Some studies have found that presence of vegetation also might reduce crime. We examined whether an association exists between two forms of green space—(1) tree canopy and (2) public parks—and crime rates in the city of Chicago. Using publicly available data, we calculated percent tree canopy, percent acreage parks, and crime rate for assault, battery, burglary, homicide, narcotics, and robbery between years 2009–2013 for each of Chicago's 801 census tracts. We used general linear modeling to determine whether tree canopy and crime rates as well as park area and crime rates were correlated after accounting for socioeconomic variables and spatial autocorrelation. An inverse association was found between percent tree canopy and crime rates for assault, battery, robbery, and narcotics. No significant association was found between crime types analyzed, with the exception of burglary, and percent park acreage.

1. Introduction

Crime prevention brings to mind policing, gun regulation, and related efforts. The physical landscape can also influence crime (Cozens, 2011). Among landscape characteristics, urban green space has been associated with reduced crime (Bogar & Beyer, 2016). Prior studies have examined the relationship between crime and vacant lot greening (Branas et al., 2011), vegetation types (Kuo & Sullivan, 2001; Wolfe & Mennis, 2012), tree canopy (Gilstad-Hayden et al., 2015; Troy, Grove, & O'Neil-Dunne, 2012), community gardens (Gorham, Waliczek, Snelgrove, & Zajicek, 2009), and parks (Groff & McCord, 2012). We investigated whether an association exists between (1) tree canopy and crime and (2) parks and crime in Chicago. Better understanding the relationship between green space and crime can inform urban planning to improve human safety and well-being.

Multiple mechanisms could explain why lower rates of specific crime types have been associated with vacant lot greening, urban tree canopy, or other forms of urban green space. Troy et al. (2012) suggest that the presence of trees, appropriately maintained, might help prevent crime by maximizing 'eyes on the street' and 'cues to care' effects. Trees with large canopies provide an appealing space for people to gather; the more people present, the more 'eyes' directly observing activities in a location. In addition to direct surveillance, well-maintained vegetation might imply surveillance to potential criminals by

'cuing' that people care for the area (Gilstad-Hayden et al., 2015; Kuo & Sullivan, 2001). As Nassauer (1995) argues, people seek information about others as they experience a landscape. An environment that appears cared for indicates human intention and that "a person has been in a place and returns frequently" (p. 162). Other mechanisms might relate to the role of vegetation in mitigating psychological precursors to violence (Kuo & Sullivan, 2001) or contributing to greater social cohesion within a community (Weinstein et al., 2015). Social cohesion involving trust has been found to be a robust predictor of lower rates of violent crime (Sampson, Raudenbush, & Earls, 1997).

Researchers have focused on different forms of green space and used various study designs to analyze relationships with crime. Branas et al. (2011) examined the effects on safety of greening vacant lots across four sections of Philadelphia. Vacant lot greening was associated with reduced gun assaults across all four city sections; vandalism decreased in one. Also in Philadelphia, Wolfe and Mennis (2012) found increased vegetation correlated with lower rates of assault, robbery, and burglary after accounting for socioeconomic variables. The relationship between green space and crime, however, might depend upon specific vegetative characteristics. In Portland, OR, Donovan and Prestemon (2012) found increased crime associated with smaller, view-obstructing trees, while larger trees were associated with reduced crime. Kuo and Sullivan (2001) examined crime rates at public housing apartment buildings in Chicago with low, medium, and high levels of vegetation. After

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<http://dx.doi.org/10.1016/j.landurbplan.2017.07.012>

Received 25 July 2016; Received in revised form 9 July 2017; Accepted 15 July 2017
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controlling for factors such as vacancy rate and building height, vegetation was a significant predictor of total, property, and violent crimes; the more greenery surrounding a building, the fewer crimes reported to police. Whereas dense shrubbery may abet crime by blocking visibility or offering a hiding place for criminals, Kuo and Sullivan (2001) conclude that "...high-canopy trees and grass may actually work to deter crime in poor inner-city neighborhoods" (p. 344).

Indeed research examining urban tree canopy and crime supports this claim. In the Baltimore region, Troy et al. (2012) found a significant inverse association between tree cover and an index of robbery, burglary, theft, and shooting in the majority of the study area after controlling for socioeconomic variables and ruralness. In the mid-size city of New Haven, CT, Gilstad-Hayden et al. (2015) found increased tree canopy cover associated with decreased violent, property, and total crime rates independent of socioeconomic characteristics and spatial autocorrelation. Similarly, (Chen et al., 2016) found a negative correlation between property crime rates and tree coverage in Vancouver.

A study in Houston, on the other hand, found no significant difference in crime rates in areas near community gardens versus those without community gardens. Residents, however, perceived a lower threat of crime in areas directly surrounding a community garden (Gorham et al., 2009). In Philadelphia, Groff and McCord (2012) found neighborhood parks to be associated with increased levels of crime in the surrounding area, although some specific park characteristics like facilities were associated with lower crime levels.

We sought to understand the relationship between green space and crime in Chicago. Various types of green space exist in Chicago, such as city parks, school grounds, community gardens, street trees, and vegetation on private lands. Our analysis focused on (1) tree canopy and (2) city parks. Data for both could readily be obtained via publicly accessible sources. Determining what association, if any, exists in Chicago between crime and each of these types of green space extends prior research. Census tracts served as our units of analysis. Based on other studies (Chen et al., 2016; Gilstad-Hayden et al., 2015; Troy et al., 2012), we hypothesized a significant inverse association between percent tree canopy and crime rate. Based on Groff and McCord's (2012) work, we hypothesized a positive association between percent area of parks within a census tract and its crime rate.

2. Methods

We examined the associations between tree canopy and crime rates as well as city parks and crime rates in Chicago's 801 census tracts using generalized linear models (GLM) while controlling for potentially confounding socioeconomic variables. We present results for two models: a non-spatial model that controls only for the socioeconomic variables, and a spatial model that additionally controls for spatial autocorrelation between census tracts as described below.

We imported crime data during the 5-year period 2009–2013 (to account for possible anomalies present in individual years) from the Chicago Data Portal (City of Chicago, 2014a) into ArcGIS 10.2.1 and queried it for assault, battery, homicide, burglary, robbery, and narcotics. The total count of each crime type was then computed for each census tract. Urban tree canopy data was obtained from a 2010 assessment completed for Cook County, IL by the University of Vermont's Spatial Analysis Lab (2015). We used the Chicago Park District parks shapefile (City of Chicago, 2014b) consisting of 556 unique park names totaling 7346 acres. These parks are managed by the Chicago Park District and vary in size, facilities, maintenance, and uses. Other forms of green space, such as community gardens, school grounds, stormwater plantings, traffic buffers, or green road medians, were not included. The percentage of a census tract polygon that is covered in urban tree canopy and the percentage that is park acreage are each considered as a predictor variable in our models below.

The following tract-level socioeconomic variables were from the "American Community Survey 5-year Data 2009–2013" (U.S. Census

Bureau, 2014): percent population below poverty, percent population 16+ unemployed, percent population 25+ without high school diploma, percent vacant housing, and percent housing renter-occupied. The former three variables were included as indicators of economic stress and the latter two as indicators of residential instability within a tract; both are possible predictors of crime. Census tract population counts were also extracted from this survey.

A generalized linear model (GLM) was run for each crime type with the amount of crime as the response variable. We adjusted for population via an offset term so that we were essentially modeling a rate: amount of crime per 1000 people. The mean of the response variable, using the log link function, is then modeled as

$$\mu_i = \frac{P_i}{1000} \exp(X\beta + \epsilon_i),$$

where μ_i is the amount of crime and p_i is the population size in census tract i , X is the matrix of predictor variables with corresponding coefficient vector β , and ϵ_i is the error term with mean 0. Adjusting for population is crucial; not doing so could lead to biased estimates of regression coefficients as areas with larger amounts of crime are those with larger population sizes. For ease of interpretation, the predictor variables are given in percentages (between 0 and 100) and then centered to have mean 0. Thus, the intercept term represents the log mean crime per 1000 people for a census tract with average values of the socioeconomic variables.

Initially, the Poisson distributional family was used for the GLM. The Poisson distribution, often used to model count data, provided an inadequate fit for most crime types due to overdispersion caused by high amounts of crime in a few census tracts. Using the negative binomial distribution, which contains an additional "dispersion" parameter, provided a better fit overall. Therefore, we used results from a negative binomial GLM.

The model described above does not account for the variability in crime due to the spatial arrangement of census tracts. Residuals in each crime model exhibited significant spatial autocorrelation as measured by Moran's I test statistic. Accounting for spatial autocorrelation is important; not doing so may also lead to biased estimates because the assumption of independent observations is violated. We can account for spatial autocorrelation in our model through the linear predictor, so that the model for the mean response becomes

$$\mu_i = \frac{P_i}{1000} \exp(X\beta + S + \epsilon_i)$$

where S denotes a zero-mean spatial random effect, and ϵ_i is normally distributed with mean 0. The specific form of S is determined by the dependence structure of spatial sites, i.e., how the value of one site is impacted by the values of nearby sites. Here, we utilize conditional autoregressive (CAR) models, which characterize the conditional distribution of a site's response given the responses of neighboring sites (Besag, 1974). This is characterized by a normal distribution with mean 0 and covariance $\sigma^2(D-\rho A)^{-1}$, where A is the adjacency matrix with entries $a_{ij} = 1$ if site i and site j are Queen contiguous neighbors (that is, they share at least one common boundary point), and $a_{ij} = 0$ otherwise, D is diagonal whose entries d_{ij} represent the number of adjacent neighbors of site i , and ρ is a number between 0 and 1 and indicates the strength of spatial dependence, with $\rho = 0$ specifying no spatial association between sites. Setting ρ and σ^2 equal 1, we can reparameterize S by taking the eigenvalue decomposition of the CAR inverse covariance matrix, and using the first few of the resulting $n = 801$ eigenvectors as additional predictors in the linear model (Boots & Tiefelsdorf, 2000; Saul, Weinberger, Ham, Sha, & Lee, 2006). Thus, $S = \alpha_1 V_1 + \alpha_2 V_2 + \dots + \alpha_k V_k$, where V_i is the eigenvector corresponding to the i 'th largest eigenvalue with associated regression coefficient α_i , and $k < n$. Each eigenvector represents a different and independent spatial pattern that explains a portion of spatial variability in the data (Griffith,

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